

KHD 2019

안저 촬영 영상 데이터



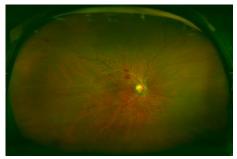
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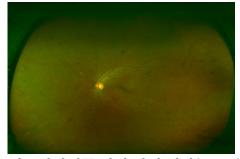
Overview

- 목표 : 안저 촬영영상 분류 모델 개발
 - 정상, 황반변성(AMD), 당뇨성망막병증(DMR), 망막정맥폐쇄(RVO) 로 구성
 - 4 multi class classification 을 목표로 함

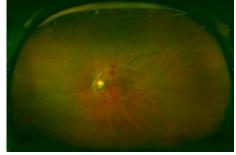


정상 광각 안저 영상





당뇨망막병증 광각 안저 영상(DMR)



망막정맥폐쇄 광각 안저 영상(RVO)



데이터셋 구성

DIRECTORY			CONTENTS
/train	/NORMAL	/Wide_NOR_xxx_R, ···	
	/AMD	/Wide_AMD_xxx_L, ···	
	/RVO	/Wide_RVO_xxx_L, ···	Jpg 확장자의 이미지 - 3900×3072×3
	/DMR	/Wide_DMR_xxx_R, ···	
/test	/NORMAL	/Wide_NOR_xxx_R, ···	
	/AMD	/Wide_AMD_xxx_R, ···	
	/RVO	/Wide_RVO_xxx_L, ···	
	/DMR	/Wide_DMR_xxx_L, ···	
/test_submit	/NORMAL	/Wide_NOR_xxx_L, ···	
	/AMD	/Wide_AMD_xxx_L, ···	
	/RVO	/Wide_RVO_xxx_R, ···	
	/DMR	/Wide_DMR_xxx_R, ···	



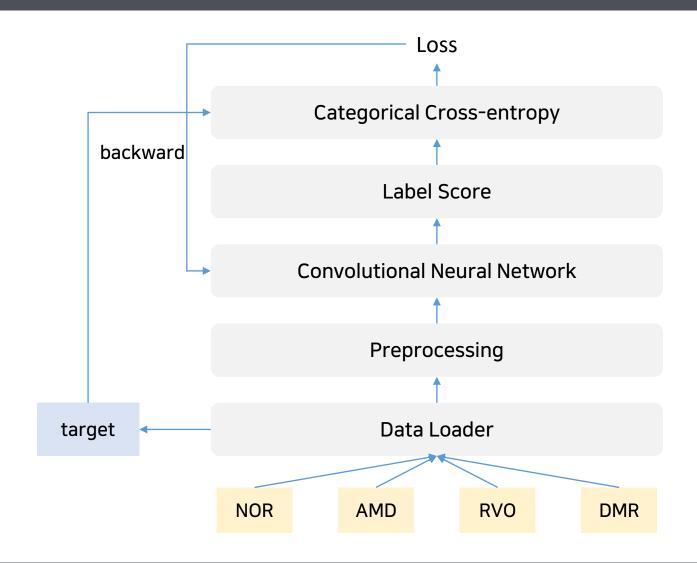
l 안저영상 질환 별 데이터 현황

안저영상 데이터 제공 표 (2018-2019 건양대병원)

질환	Train 수량 (장)	Test 수량 (장)	비율 (%)
정상	999	110	26
황반변성(AMD)	901	81	23
당뇨망막병증(DMR)	1,570	175	40
망막정맥폐쇄(RVO)	443	49	11



시스템 베이스라인





| CNN 모델 샘플 코드

```
def dataset_loader(img_path, rescale=RESCALE, resize_factor=RESIZE):
t1 = time.time()
print('Loading training data...\#n')
p_list = [os.path.join(dirpath, f) for dirpath, dirnames, files in os.walk(img_path) for f in files if all(s in f for s in ['.jpg'])]
p_list.sort()
images = []
Tabels = []
for i, p in enumerate(p_list):
    im = cv2.imread(p, 3)
    if not (resize_factor == 1.):
        im = image_preprocessing(im, rescale=rescale, resize_factor=resize_factor)
     images.append(im)
    I = Label2Class(p.split('/')[-2])
     Tabels.append(T)
 images = np.array(images)
 jabels = np.array(labels)
t2 = time.time()
print('Dataset prepared for' ,t2 -t1 ,'sec')
print('Images:' ,images.shape ,'np.array.shape(files, views, width, height)')
print('Labels:', labels.shape, ' among 0-3 classes')
return images. Tabels
```



| CNN 모델 샘플 코드

```
l<mark>def cnn_sample(in_shape):  # E</mark>xample CNN
## Sample code
num_classes = 4
model = Sequential()
model.add(Conv2D(filters=16, kernel_size=(5, 5), padding='same', input_shape=in_shape))
model.add(BatchNormalization(axis=-1))
model.add(ReLU())
model.add(Conv2D(filters=32, kernel_size=(5, 5), padding='same'))
model.add(BatchNormalization(axis=-1))
mode(.add(ReLU())
model.add(ZeroPadding2D(padding=((0, 0), (0, 1))))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(filters=64, kernel_size=5, padding='same'))
mode1.add(ReLU())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(filters=128, kernel_size=6, padding='same'))
model.add(BatchNormalization(axis=-1))
mode(.add(ReLU())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(filters=256, kernel_size=5, padding='same'))
model.add(BatchNormalization(axis=-1))
model.add((ReLU()))
model.add(Flatten())
model.add(Dense(100, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))
return model
```





NSML Leaderboard

Categorical accuracy

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

Sensitivity

: 모든 positive case 중 positive라고 예측한 결과

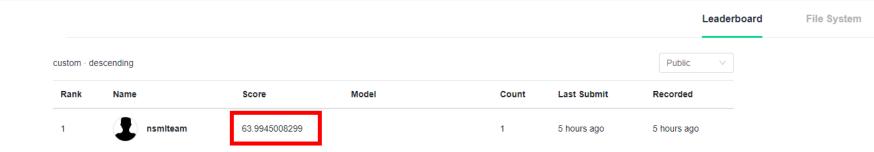
$$Sensitivity = \frac{TP}{TP + FN}$$

Specificity

:모든 negative case 중 negative라고 예측한 결과

$$specificity = \frac{TN}{TN + FP}$$

NSML Leaderboard



Score: aa.aannnnpppp

AccuracySensitivitySpecificity

→ Accuracy를 기준으로 ranking 1-5까지는 sensitivity와 specificity 함께 평가





